Journal of Forecasting
J. Forecast. **31**, 736–756 (2012)
Published online 8 November 2011 in Wiley Online Library
(wileyonlinelibrary.com) **DOI**: 10.1002/for.1253

# Are Analysts' Loss Functions Asymmetric?

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ABSTRACT
Despite displaying a statistically significant optimism bias, analysts' earnings forecasts are an important input to investors' valuation models. Understanding the possible reasons for any bias is important if information is to be extracted from earnings forecasts and used optimally by investors. Extant research into the shape of analysts' loss functions explains optimism bias as resulting from analysts minimizing the mean absolute forecast error under symmetric, linear loss functions. When the distribution of earnings outcomes is skewed, optimal forecasts can appear biased. In contrast, research into analysts' economic incentives suggests that positive and negative earnings forecast errors made by analysts are not penalized or rewarded symmetrically, suggesting that asymmetric loss functions are an appropriate characterization. To reconcile these findings, we exploit results from economic theory relating to the Linex loss function to discriminate between the symmetric linear loss and the asymmetric loss explanations of analyst forecast bias. Under asymmetric loss functions optimal forecasts will appear biased even if earnings outcomes are symmetric. Our empirical results support the asymmetric loss function explanation. Further analysis also reveals that forecast bias varies systematically across firm characteristics that capture systematic variation in the earnings forecast error distribution. Copyright © 2011 John Wiley & Sons, Ltd.

KEY WORDS asymmetric loss functions; earnings forecast bias; financial analysts; Linex

## INTRODUCTION

Financial analysts' forecasts of corporate earnings are an important input to investors' valuation models, despite extensive research from a variety of countries and time periods suggesting that such forecasts are irrational: analysts' earnings forecasts appear to be both biased and inefficient (e.g. DeBondt and Thaler, 1990; Brown, 1993; Capstaff *et al.*, 1995, 1998, 2001). More recent research suggests that the statistical bias and inefficiency of earnings forecasts could in fact be rational and due to the

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loss functions underpinning analysts' forecast choices (e.g. see Ramnath *et al.*, 2008, for a review). An analyst's 'optimal' earnings forecast will depend on the subjective probability distribution of prospective forecast errors and on the loss function. Therefore, in order to interpret and use earnings forecasts in company valuation, investors should understand analysts' loss functions and the resulting properties of earnings forecasts (Lambert, 2004). This paper contributes to the literature by presenting evidence indicating that the bias in analysts' earnings forecasts is related to asymmetric loss functions.

Our results contrast with arguments elsewhere in the literature that it is asymmetry in the distribution of realized earnings outcomes, not in financial analysts' loss functions, that drives analyst forecast bias. In particular, Gu and Wu (2003) argue that forecast bias is only irrational under quadratic loss and that if analysts have symmetric, linear loss functions then biased earnings forecasts can be rational. They find that earnings forecast bias is associated with skewness in the distribution of earnings, which is consistent with the presence of *symmetric* linear loss functions where analysts minimize the mean absolute forecast error. Consistent with a linear symmetric loss function, Basu and Markov (2004) find that the null hypothesis of rationality is rejected less frequently when least absolute deviation regression is used in place of ordinary least squares regression. However, they do not test the symmetric linear function explanation of forecast bias against the alternative that analysts have asymmetric loss functions and, as noted by Lambert (2004), Basu and Markov (2004) provide limited evidence to support the premise that analysts' loss functions are linear and symmetric.

The idea that financial analysts bear asymmetric losses for positive and negative earnings forecast errors (i.e. under- and over-predictions of earnings realizations, respectively) receives strong support in prior research into analysts' incentives and the institutional environment in which they produce their forecasts.[1] Asymmetric costs and benefits associated with analyst forecast errors can arise as a result of the relation between sell-side securities firms and buy-side investors. For example, evidence suggests that optimistic earnings forecasts are profitable to sell-side firms because they are more likely to result in trading commission (Jackson, 2005).[2] Asymmetric costs and benefits associated with positive and negative forecast errors might also arise as a result of the business relationships between analysts (or the sell-side securities firms they work for) and the companies that analysts follow. For example, evidence suggests that when investment banking ties exist between a company and the securities firms employing analysts, analysts' earnings forecasts are more optimistic (Dugar and Nathan, 1995; Lin and McNichols, 1998) and analysts are less likely to issue timely unfavourable forecasts (O'Brien *et al.*, 2005). Consistent with these studies, Hong and Kubik (2003) report that, after controlling for forecast accuracy, analysts who issue more optimistic forecasts are more likely to have improved career prospects.[3]

A further incentive for analysts to issue optimistic forecasts arises because company management potentially supplies useful information to analysts. Lim (2001) reports that company managers may

[1] Asymmetric loss functions stem from human evaluations of probabilities and the costs and benefits of associated outcomes not being strictly independent of each other—a notion firmly established in the psychology literature (see Weber, 1994). Due to the appeal of the idea that over-predictions and under-predictions are not penalized equally in many decision-making contexts, asymmetric loss is an area receiving increasing attention in the forecasting literature more generally (e.g. see Elliott *et al.*, 2005; Demetrescu, 2007; Patton and Timmerman, 2007a,b).

[2] Jackson (2005) also shows that in the presence of asymmetric information about analyst motives analysts' response to such incentives can also be reconciled with their need to maintain credibility.

[3] See also Ashiya (2009) for a discussion of how employers' views may create biases in macroeconomic forecasts.



**DOI**: 10.1002/for

restrict access to valuable information if analysts issue pessimistic earnings forecasts.[4] Significant regulatory attention has been directed towards these issues (such as the 2004 guidance on conflicts of interest in sell side research issued in the UK by the Financial Services Authority and Regulation Fair Disclosure in the USA), though the evidence on the effectiveness of these interventions is mixed (e.g. Bradshaw, 2009a; Barniv *et al.*, 2009).

Smith Raedy *et al.* (2006) exploit asymmetric loss functions in understanding the properties of financial analysts' earnings forecasts; however, their focus is on possible inefficiency of analysts' forecasts and, in particular, on evidence of under-reaction to prior forecast errors.[5] They present evidence consistent with analysts facing asymmetric reputational costs for forecast inaccuracy, where the costs depend on whether or not forecast errors confirm as correct the direction of analysts' earlier reactions to news. They demonstrate that the degree of under-reaction increases with the forecast horizon, in a similar manner to the positive relation between optimism bias and forecast horizon documented by Kang *et al.* (1994). In contrast to Smith Raedy *et al.* (2006), our paper focuses on bias (rather than inefficiency) in analysts' forecasts, and the extent to which it can be attributed to analysts having asymmetric loss functions.

Economic theory predicts that when analysts have asymmetric loss functions (more specifically, the Linex loss function in our case), the degree of rational bias in forecasts will be related to the expected variance of forecast errors; however, the bias will not be related to the expected variance of earnings forecast errors when analysts have symmetric loss functions. Hence our analysis allows us to test the hypothesis that forecast bias results from asymmetric loss functions against the alternative of symmetric loss functions.

In contrast to research suggesting that analysts' loss functions are symmetric, our results are consistent with analysts minimizing asymmetric loss functions. More specifically, the sign of the coefficient on expected forecast error variance in our tests allow us to reject the symmetric linear loss function explanation and suggests that positive forecast errors (pessimistic forecasts) are penalized more heavily than negative forecast errors (optimistic forecasts). This result is in accordance with the research into analysts' economic incentives affecting the earnings forecasting task (discussed above) and contrasts with the conclusions of Gu and Wu (2003) and Basu and Markov (2004) that analysts are penalized equally for positive and negative earnings forecast errors under symmetric linear loss. We also analyse the determinants of earnings forecast errors through an analysis of portfolios formed on the basis of the book-to-price ratio and market capitalisation—two firm characteristics that are known determinants of earnings forecast bias and that are also related to variance and skewness in earnings. We find that forecast bias is also associated with book-to-price and market capitalization, but the dominant role of expected forecast error variance in explaining forecast bias is robust across these characteristic portfolios.

The remainder of the paper is organized as follows. In the next section, we discuss the theory of asymmetric loss functions and derive empirical predictions based on the Linex loss function that distinguish between linear and asymmetric loss. The third section discusses our empirical research

[4] See Bradshaw (2009b) for a detailed discussion of research into analysts' incentives and the role they may play in explaining empirical regularities in this literature.

[5] In research developed concurrently with an earlier version of this paper, Markov and Tan (2005) also find evidence of asymmetric loss employing the approach of Elliott *et al.* (2005). This approach effectively reverse engineers the forecast to recover the loss function shape parameter. However, whether the asymmetry is consistent with optimism bias depends on the specification of the model they estimate. The same approach of 'backing out' loss function parameters has also been employed to investigate macroeconomic growth forecasts (e.g. Christodoulakis and Mamatzakis, 2008; Patton and Timmermann, 2007b).



**DOI**: 10.1002/for

design and describes our dataset. In the fourth section we report our empirical results. Finally, in the fifth section we present our conclusions and suggestions for further research.

## FINANCIAL ANALYSTS' LOSS FUNCTIONS AND EARNINGS FORECAST BIAS

If financial analysts have quadratic loss functions and attempt to minimize the mean squared error (MSE), then their optimal earnings forecast is the conditional mean (expected value) of the earnings distribution and observed forecast bias represents evidence of analyst irrationality. Under asymmetric loss, however, unbiasedness—like many other commonly used optimality properties of MSE—is an unreliable benchmark for the empirical evaluation of forecasts (Patton and Timmermann, 2007a). While there are strong suggestions in the existing literature that analysts' incentives are likely to lead to asymmetric costs associated with positive and negative earnings forecast errors, the limited research that studies analysts' loss functions as an explanation for analyst forecast bias has advanced linear symmetric loss functions as an explanation of earnings forecast bias (Gu and Wu, 2003; Basu and Markov, 2004).

If the subjective probability distribution of earnings is skewed, rational forecasts with symmetric loss functions are biased, unless the loss function is quadratic (Granger, 1969; Gu and Wu, 2003; Basu and Markov, 2004). In contrast to the quadratic loss function case, rational analysts with symmetric linear loss functions minimize the mean absolute value of anticipated forecast errors (MAE). Similar to quadratic loss functions, symmetric linear loss functions weight equally positive and negative forecast errors of the same magnitude, though in contrast to quadratic loss functions, symmetric linear loss functions attach relatively lower weight to more extreme forecast errors.[6]

With symmetric linear loss functions the optimal forecast is the conditional median of the earnings distribution and the expected value of the median forecast error is zero. The mean forecast error will differ from zero and earnings forecasts will be biased only if the conditional mean and the conditional median differ. In other words, if analysts' loss functions are symmetric, then the optimal forecast bias depends on skewness in the distribution of earnings, but not on the variance of earnings. Conversely, as Patton and Timmermann (2007a, p. 888) show, optimal forecasts are unbiased only when both the forecast variable is distributed symmetrically *and* the loss function is symmetric, i.e. under conditions of 'double symmetry'.

The precise properties of forecast errors and the determinants of the optimal bias will depend on both the distribution of earnings and on the functional form and parameters of the loss function (Keane and Runkle, 1998; Elliott *et al.*, 2005; Patton and Timmermann, 2007a). However, a general result is that under asymmetric loss functions the optimal degree of forecast bias will depend on the expected variance of the distribution of forecast errors and on higher moments of the forecast error distribution (Granger, 1969; Patton and Timmermann, 2007a).

Analytical results on the dependence between optimal forecast bias and forecast error variance can be obtained by assuming specific functional form for the loss function. Christofferson and Diebold (1996, 1997) analyze optimal forecast bias under the Linex loss function and assuming conditional normality of the forecast error distribution (Varian, 1974; Zellner, 1986). The Linex loss function relaxes the assumption of constant marginal cost of forecast errors in the Lin-Lin specification and allows for asymmetry of marginal cost (Varian, 1974; Zellner, 1986).

[6] Though Granger (1969) proposes a piecewise linear (Lin-Lin) loss function that weights positive and negative forecast errors of similar magnitude differently.



**DOI**: 10.1002/for

Assume that the variable to be forecast is earnings at time $t$, denoted $y_t$. The Linex loss function has the following form:

$$L = \frac{e^{\alpha x_t} - \alpha x_t - 1}{\alpha^2} \tag{1}$$

where $\alpha$ is a constant parameter and $x_t$ is the forecast error at time $t$, defined as $x_t \equiv y_t - f_t$, where $f_t$ is the forecast. The shape parameter $\alpha$ determines the degree of asymmetry while its sign determines the direction of the asymmetry. A convenient property of the Linex loss function is that it nests the quadratic loss function as $\alpha \to 0$.[7]

Under the Linex loss function, optimistic forecasts (negative forecast errors) are more costly than pessimistic forecasts (positive forecast errors) when $\alpha < 0$. In this case, the loss is approximately exponential in $x$ if $x < 0$, and approximately linear in $x$ if $x > 0$. Conversely, where $\alpha > 0$, loss is exponential to the right of the origin and linear to the left. In this case, pessimistic forecasts (positive forecast errors) are more costly than optimistic forecasts (negative forecast errors).

Assume initially that earnings, $y_{t,}$ are generated by a conditional Gaussian process. Christofferson and Diebold (1996, 1997) show that under the Linex loss function (1), the optimal $h$-period-ahead forecast, $f_{t,t+h}$, is given by

$$f_{t,t+h} = E_t(\mu_{t+h}) + \frac{\alpha}{2} E_t(\sigma^2_{t+h})_t \tag{2}$$

where $E_t(\mu_{t+h})$ is the expectation of the mean of $y_{t+h}$ conditional on information at time $t$ (and is the optimal forecast under quadratic loss) and $E_t(\sigma^2_{t+h})$ is the expectation of the conditional error variance over the $h$ periods. Expression (2) tells us that the optimal forecast for a rational analyst with an asymmetric loss function, given by the Linex function (1), differs from the conditional mean, i.e. the forecast is biased.[8] It is optimal for the analyst to produce optimistic forecasts if $\alpha > 0$. Christofferson and Diebold (1996, 1997) also show that the *ex post* forecast error, $x_t$ is given by

$$x_t = -\frac{\alpha}{2} E_t(\sigma^2_{t+h}) + z_t \tag{3}$$

where $z_t$ is a zero mean moving average error process of order $h - 1$. Note also that if the conditional variance of the forecast error is time varying then optimal forecasts exhibit time-varying bias, conditional on the time-varying forecast error variance.

Expressions (2) and (3) indicate that the optimal bias under asymmetric loss depends positively on the loss function parameter, $\alpha$, and on the variance of the forecast error. The optimal forecast expression (2) assumes that the outcome (earnings) series, $y_{t,}$, is a conditional Gaussian process. If we relax this assumption, it is possible to show that the optimal forecast and the forecast bias depend on both the variance and the skewness of the forecast error process. For example, Christodoulakis (2005) derives a closed-form solution assuming non-normal distributions in the form of the Gram–Charlier class. In this case the forecast error is given by

$$x_t = G\left[E_t\left(\sigma^2_{t+h}\right), E_t\left(\sigma^3_{t+h}\right)\right] + z^*_t \tag{4}$$

[7] As $\alpha \to 0$, the numerator and the denominator of (1) tend to zero. Consequently, as $\alpha \to 0$, we employ L'Hospital's rule to obtain the quadratic form.

[8] Patton and Timmermann (2007a) also show that optimal forecasts under Linex are biased for nonlinear data-generating processes. Furthermore, they show that other optimality properties under quadratic loss do not hold in the context of the Linex loss function. For instance, non-zero autocovariances in one-step-ahead forecast errors are shown to exist and the variance of the forecast error is sometimes a *decreasing* function of the forecast horizon.



**DOI**: 10.1002/for

where $z_t^*$ is a moving average error process, $E_t(\sigma_{t+h}^3)$ is the expectation of conditional skewness of the forecast error and $G$ is a nonlinear, positive function of both the conditional variance and the conditional skewness of the forecast error (see Appendix for the proof).

Expressions (3) and (4) have important empirical implications, given that the distribution of earnings forecast errors is non-normal (e.g. Abarbanell and Lehavy, 2003). Under asymmetric loss, if $\alpha > 0$ then forecast bias is expected to depend positively on the variance of the forecast error. The above analysis also predicts that forecast errors will be positively related to skewness, although the association will be weak if the magnitude of $\alpha$ is small. This implies that a test of whether analysts' loss functions are asymmetric is to examine dependence between forecast errors and proxies for the conditional variance and conditional skewness of forecast errors. If only skewness is a significant determinant of forecast errors then this is consistent with analysts minimizing absolute forecast errors. If the forecast error variance is a significant determinant of forecast errors, then the hypothesis that analysts minimize absolute forecast error can be rejected in favour of an asymmetric loss function, under the maintained assumption of rational expectations. Depending on the functional form of the asymmetric loss function, bias might also depend on higher moments of the distribution of forecast errors, including skewness.[9]

## RESEARCH DESIGN

### Model specification

We assume that loss functions adjust for any scale-related component of 'raw' earnings per share forecast errors and that the price-scaled earnings forecast error is the relevant input to the loss function.[10] However, while our main tests employ price-scaled forecast errors, in unreported sensitivity tests we also obtained results using unscaled data using simulation techniques that allow for heteroscedasticity and non-normality. Our main estimating equation is as follows:

$$ERROR_{it} = b_0 + \lambda_1 ERRVAR_{it} + \lambda_2 ERRSKEW_{it} + \varepsilon_{it} \tag{5}$$

where *ERROR* is defined as actual quarterly earnings minus the median of all forecasts of quarterly earnings issued within 90 days of the earnings announcement, scaled by beginning-of-period stock price. Although analysts' loss functions may vary systematically in the cross-section (e.g. Lambert, 2004), our use of the consensus as a proxy for the marginal or representative analyst is consistent with prior research in this area (e.g. Gu and Wu, 2003; Basu and Markov, 2004).[11] We measure error variance (*ERRVAR*) as the unstandardized variance of price-scaled forecast errors (multiplied by 100) in the preceding eight periods. Similarly, we measure skewness (*ERRSKEW*) as the sum of the cubed deviations from the mean price-scaled error for the eight quarters prior to quarter $t$, multiplied by 100.

To allow comparability with prior empirical research, we also augment regression (1) by including a number of control variables capturing other potential determinants of forecast bias: *lnMVAL*

[9] Although Gu and Wu (2003) include measures of earnings variability and forecast variability as control variables in their test of the MAE loss function, we include the variance of the forecast error as the central test of an asymmetric loss function. We note that theoretically it is the moments of forecast errors that are relevant determinants of any bias, and not the distribution of the variable to be forecast (i.e. earnings) per se.

[10] For example, suppose that intrinsic value is a constant multiple of forecast earnings per share. The per share intrinsic value estimation error is proportional to the scaled forecast error and the relevant input to the loss function will be price-scaled forecast errors.

[11] We also conduct robustness tests using individual forecasts. These tests are discussed further below.



**DOI**: 10.1002/for

is the natural logarithm of market value at the beginning of quarter $t$ and is included to control for the possibility that analysts issue more biased forecasts for smaller companies, e.g. to obtain access to management where less information is available (Francis and Willis, 2001). *lnANFLL* is the natural log of the number of analysts issuing forecasts for firm $i$ in quarter $t$ and allows for the possibility that forecasts are more optimistic for firms that attract higher analyst following (e.g., Das *et al.*, 1998). We also include *LOSS* as an indicator variable (equal to 1 if the consensus forecast of earnings is negative, zero otherwise) because it has been argued that forecasts of losses are more optimistic (e.g. Duru and Reeb, 2002). *SUE*1 and *SUE*2 are included to control for analyst under-reaction (e.g. Abarbanell and Bernard, 1992) and are defined as, respectively, the one-period and two-period lagged earnings surprise based on a seasonal random walk model. *ERROR*, *SUE*1 and *SUE*2 are scaled by stock price in the month preceding quarter $t$.

**Data**

Owing to data requirements (particularly the need for a sufficiently long time series of earnings and forecasts for each firm to obtain measures of error variance and skewness), our sample is for US firms drawn from the I/B/E/S detail history files (which have been found to be more accurate than other sources of earnings forecasts—see Ramnath *et al.*, 2005) and from Compustat for the period 1983–2008. Individual analysts' quarterly earnings per share forecasts, actual earnings per share, earnings announcement dates and stock price data are obtained from I/B/E/S. We require each firm to have at least eight consecutive quarters' actual earnings and forecast data in order to generate our measures of forecast error variance and skewness. Data for the book-to-market ratio are obtained from Compustat.

In order to remove potential data errors, we winsorize the error and earnings related variables at the 1st and 99th percentiles, in line with previous research (e.g. Abarbanell and Lehavy, 2003). Our results are robust to alternative outlier deletion procedures (e.g. removing observations in the 5th and 95th percentiles).

**Descriptive statistics**

Our final sample comprises 100,160 firm quarters for 5,101 firms. Table I, panel A, provides summary statistics for our sample. In line with prior research (e.g. Basu and Markov, 2004), the sample-wide distribution of forecast errors is negatively skewed, with the mean forecast error being negative, indicating an optimism bias (which is also in line with the European evidence reported in Capstaff *et al.*, 2001) and the median forecast error being slightly positive. Our measures of firm-specific expected error variance and expected error skewness have coefficients of variation of, respectively, around 4.11 and 7.25 while *ERRSKEW* is negative on average, consistent with expectations. In respect of the control variables, the descriptive statistics for *LOSS* and *FLLW* show that approximately 10% of the firms in our sample were forecast to make a loss and the average number of analysts following each firm in quarter $t$ is 9. Panel B of Table I provides reassurance that the forecast error distribution in our sample is broadly consistent with the distribution reported in prior literature by comparing our sample with that in Abarbanell and Lehavy (2003). The comparison shows that the level of optimism in our sample is lower, as measured by the mean forecast error of −0.078 versus −0.126 and the median of 0.021 versus 0.000); overall, however, the two samples are similar, despite the forecast data being from different data sources and our data covering a longer time period.

Panel C of Table I reports the full sample correlations between variables. Particularly noteworthy is the negative correlation of −0.8411 between *ERRVAR* and *ERRSKEW*. This is partly attributable

Table I. Panel A: Descriptive statistics ($n$ = 100,160)

| Variable | Mean | Median | SD | Skewness |
|---|---|---|---|---|
| *ERROR* | −0.0776 | 0.0214 | 1.0116 | −4.55 |
| *ERRVAR* | 0.0927 | 0.0034 | 0.4271 | 6.75 |
| ERRSKEW | −0.0036 | 0.0000 | 0.0261 | −8.12 |
| *MVAL* (mil \$) | 6060 | 1272 | 39237 | 201.60 |
| *ANFLL* | 9.07 | 6.00 | 8.6064 | 2.47 |
| *LOSS* | 0.1021 | 0.00 | 0.3028 | 2.63 |
| *SUE1* | 0.0164 | 0.1584 | 1.7874 | −0.95 |
| *SUE2* | 0.0310 | 0.1619 | 1.7297 | −0.88 |

Panel B: Comparison of forecast error (*ERROR*) distribution with Abarbanell and Lehavy's (2003) sample

| | Our sample ($N$ = 100,160) | Abarbanell and Lehavy (2003) ($N$ = 33,548) |
|---|---|---|
| Mean | −0.078 | −0.126 |
| Median | 0.021 | 0.000 |
| % positive | 55% | 48% |
| % negative | 38% | 40% |
| % zero | 7% | 12% |
| 5th percentile | −1.068 | −1.333 |
| 10th percentile | −0.492 | −0.653 |
| 25th percentile | −0.084 | −0.149 |
| 75th percentile | 0.142 | 0.137 |
| 90th percentile | 0.409 | 0.393 |
| 95th percentile | 0.725 | 0.684 |

Panel C: Correlation coefficients

| | *ERROR* | *ERRVAR* | ERRSKEW | *lnMVAL* | *lnANFLL* | *LOSS* | *SUE1* |
|---|---|---|---|---|---|---|---|
| *ERRVAR* | −0.1606‡ | | | | | | |
| *ERRSKEW* | 0.1409‡ | −0.8411‡ | | | | | |
| *lnMVAL* | 0.1122‡ | −0.1691‡ | 0.1158‡ | | | | |
| *lnANFLL* | 0.0385‡ | −0.0815‡ | 0.0601‡ | 0.5395‡ | | | |
| *LOSS* | −0.1380‡ | 0.1781‡ | −0.0993‡ | −0.2282‡ | −0.0683‡ | | |
| *SUE1* | 0.1687‡ | −0.0152‡ | 0.0432‡ | 0.0873‡ | 0.0304‡ | −0.2212‡ | |
| *SUE2* | 0.1155‡ | −0.0362‡ | 0.0477‡ | 0.0957‡ | 0.0388‡ | −0.1908‡ | 0.4635‡ |

*Note*: In panel C, we compare our sample with that of Abarbanell and Lehavy (2003). Abarbanell and Lehavy (2003) use the Zacks database from 1985 to 1998; we use I/B/E/S from 1983 to 2008. Both samples are winsorized at the 1st and 99th percentiles.

‡Indicates significance at the 0.001 level.

to the estimation of correlation coefficients over the full panel when there is time series dependence in these instruments due to the common information used in estimating adjacent time series observations. Nevertheless, the negative correlation suggests the possibility that skewness serves as a proxy for variance in prior research. Since dependence of the forecast error on error variance is the key empirical prediction that distinguishes the symmetric (linear) loss explanation of forecast bias from the asymmetric loss explanation, this characteristic of the data points to the importance of controlling for variance in evaluating these two competing explanations.



**DOI**: 10.1002/for

## RESULTS

### Main regression results

Our main regression results are reported in Table II. We report our three main models (models 1–3), which include one or both of *ERRVAR* and *ERRSKEW*; we then report these models with control variables in models 4–6. In view of the non-normality in the distribution of forecast errors in

Table II. Price-deflated forecast error regressions

Model 1:
$$ERROR_{it} = b_0 + \lambda_1 ERRVAR_{it} + \varepsilon_{it}$$
Model 2:
$$ERROR_{it} = b_0 + \lambda_1 ERRVAR_{it} + \lambda_2 ERRSKEW_{it} + \varepsilon_{it}$$
Model 3:
$$ERROR_{it} = b_0 + \lambda_2 ERRSKEW_{it} + \varepsilon_{it}$$
Model 4:
$$ERROR_{it} = b_0 + \lambda_1 ERRVAR_{it} + b_1 ln\,MVAL_{it} + b_2 ln\,ANFLL_{it} + b_3 LOSS_{it} + b_4 SUE1_{it} + b_5 SUE2_{it} + \varepsilon_{it}$$
Model 5:
$$ERROR_{it} = b_0 + \lambda_1 ERRVAR_{it} + \lambda_2 ERRSKEW_{it} + b_1 ln\,MVAL_{it} + b_2 ln\,ANFLL_{it} + b_3 LOSS_{it} + b_4 SUE1_{it} + b_5 SUE2_{it} + \varepsilon_{it}$$
Model 6:
$$ERROR_{it} = b_0 + \lambda_2 ERRSKEW_{it} + b_1 ln\,MVAL_{it} + b_2 ln\,ANFLL_{it} + b_3 LOSS_{it} + b_4 SUE1_{it} + b_5 SUE2_{it} + \varepsilon_{it}$$

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| Constant | −0.0424‡ | −0.0433‡ | −0.0579‡ | −0.3022‡ | −0.3047‡ | −0.3426‡ |
| | (9.97) | (9.87) | (13.03) | (12.87) | (12.92) | (13.91) |
| | [13.13] | [13.36] | [18.13] | [20.38] | [20.53] | [23.23] |
| *ERRVAR* | −0.3805‡ | −0.3412‡ | — | −0.3216‡ | −0.2784‡ | — |
| | (9.72) | (4.96) | — | (8.63) | (4.10) | — |
| | [51.51] | [24.98] | — | [43.28] | [20.29] | — |
| *ERRSKEW* | — | 0.7631 | 5.4518‡ | — | 0.8263 | 4.5899‡ |
| | — | (0.73) | (9.03) | — | (0.82) | (8.18) |
| | — | [3.42] | [45.04] | — | [3.75] | [38.34] |
| *lnMVAL* | — | — | — | 0.0438‡ | 0.0441‡ | 0.0484‡ |
| | — | — | — | (12.87) | (12.91) | (13.45) |
| | — | — | — | [18.98] | [19.10] | [20.98] |
| *lnANFLL* | — | — | — | −0.0229‡ | −0.0230‡ | −0.0237‡ |
| | — | — | — | (4.66) | (4.68) | (4.69) |
| | — | — | — | [5.68] | [5.71] | [5.85] |
| *LOSS* | — | — | — | −0.2129‡ | −0.2171‡ | −0.2539‡ |
| | — | — | — | (8.02) | (8.06) | (9.12) |
| | — | — | — | [19.52] | [19.80] | [23.43] |
| SUE1 | — | — | — | 0.0750‡ | 0.0746‡ | 0.0717‡ |
| | — | — | — | (13.12) | (12.84) | (12.73) |
| | — | — | — | [37.95] | [37.63] | [36.21] |
| *SUE2* | — | — | — | 0.0181‡ | 0.0179‡ | 0.0175‡ |
| | — | — | — | (3.09) | (3.07) | (3.00) |
| | — | — | — | [8.90] | [8.83] | [8.59] |



**DOI**: 10.1002/for

Table II. *Continued*

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| $R^2$ | 0.0258 | 0.0259 | 0.0199 | 0.0638 | 0.0639 | 0.0600 |
| $F$- value | 94.46 | 48.70 | 81.56 | 97.49 | 85.34 | 93.84 |
| $N$ | 100,160 | 100,160 | 100,160 | 100,160 | 100,160 | 100,160 |

*Notes:*
Absolute $t-$statistics based on firm-clustered standard errors are in parentheses; OLS $t$-statistics are in square brackets.
*ERROR* is actual quarterly earnings taken from I/B/E/S minus the median of all forecasts of quarterly earnings issued within 90 days of the earnings announcement, scaled by stock price at the beginning of the quarter, multiplied by 100.
*ERRVAR* is the second moment of the price-deflated previous eight quarters' forecast errors, multiplied by 100.
*ERRSKEW* is the third moment of the price-deflated previous eight quarters' forecast errors, multiplied by 100.
*lnMVAL* is the natural log of market value of common equity at the beginning of the quarter (in $ millions).
*lnANFLL* is the natural log of the number of analysts issuing forecasts for each firm in the quarter the forecast falls in.
*LOSS* is an indicator variable equal to 1 if the consensus forecast of earnings is negative, zero otherwise.
*SUE1* and *SUE2* are the price-deflated seasonal unexpected earnings from a random walk at quarters $t-1$ and $t-2$, respectively, multiplied by 100.
‡ Indicates coefficients are significantly different from zero at the 0.01 level in two-tailed tests based on firm-clustered standard errors.

Table I, the possibility exists that inferences are sensitive to heteroscedasticity and non-normality in regression errors.[12] Recent research also points to the need to control for cross-section and time series dependence in panel datasets (Petersen, 2008). Therefore we report both OLS $t$-statistics (as in Gu and Wu, 2003) and $t$-statistics based on Rogers' (1993) 'clustered' standard errors.[13] Petersen (2008) finds standard errors clustered by firm to be unbiased in the presence of time series correlation within firms, in contrast to OLS and Fama–MacBeth (1973) regressions, which may be downwardly biased in panel datasets.

Table II indicates that the clustered $t-$statistics, based on standard errors adjusted to allow for time series dependence in firm residuals, are often very much lower than the OLS $t-$statistics, and inferences regarding the significance of *ERRSKEW* are sensitive to the choice of test statistic. We therefore rely on the more conservative clustered $t$-statistics where relevant. Models 3 and 6 reveal a significant positive association between *ERROR* and *ERRSKEW* when *ERRVAR* is excluded. Results for models 1 and 3 indicate that if *ERRSKEW* is replaced by *ERRVAR*, model specification improves (without control variables the adjusted $R^2$ statistic increases from 1.99% to 2.58%). The signs of the coefficients on *ERRVAR* are negative, as predicted if positive forecast errors are more costly to analysts than negative forecast errors. Results for models 2 and 5 indicate that the statistical significance of *ERRVAR* remains, even after controlling for *ERRSKEW*, and despite the high correlation between *ERRVAR* and *ERRSKEW* that would be expected to bias $t-$statistics towards zero.[14] Note, however,

[12] Breusch–Pagan (1979) tests reject the null of constant variance of residuals in all reported models.
[13] We also examined the sensitivity of inferences to the use of the delete-group jackknife standard errors (Shao and Rao, 1993) and to the use of exact critical values for robust standard errors obtained from the Wild bootstrap methodology (discussed further below) and our results are robust under both approaches. Although critical values obtained from the bootstrap methodology are much higher than classical values, indicating that non-normality is a significant problem, the main inferences are unchanged. Indeed, they are reinforced.
[14] Despite the high univariate correlation between *ERRVAR* and *ERRSKEW*, all variance inflation factors in the multivariate analyses were well under the commonly used threshold of 10 (e.g. Chatterjee and Price, 1977).



**DOI**: 10.1002/for

that when *ERRVAR* is included in the model, the coefficient on *ERRSKEW* in models 2 and 5 becomes insignificant, in contrast to the positive significant coefficients in models 3 and 6.

Generally, the estimates in Table II indicate that our results are not sensitive to inclusion of control variables.[15] Inferences regarding the significance of *ERRVAR* and *ERRSKEW* are identical for models 1–3 and for models 4–6; i.e. *ERRVAR* is always negative and significant, whereas *ERRSKEW* is insignificant in the presence of *ERRVAR*. Therefore, in subsequent tests, we focus on models 1–3.

The estimated parameters for the control variables in models 4–6 are generally in line with the findings in prior research. Forecast errors are positively related to firm size (as captured by *lnMVAL*) in each of the reported models, suggesting that analysts are more optimistic when forecasting earnings of smaller firms. We further examine this issue below. There are significant negative coefficients on the analyst following variable (*lnANFLL*) and the loss variable (*LOSS*), both of which are consistent with prior research (e.g. Gu and Wu, 2003). Like many previous studies (e.g. Abarbanell and Bernard, 1992; Easterwood and Nutt, 1999), there is also evidence of under-reaction to prior period earnings changes—coefficients on both *SUE*1 and *SUE*2 are significant and positive in each of models 4–6.[16]

Overall, we interpret the results in Table II as providing strong support for our hypothesis that analysts have asymmetric loss functions, rather than linear symmetric loss functions. If analysts' loss functions are linear and symmetric, forecast errors should be a function of *ERRSKEW* but not *ERRVAR*, whereas asymmetric loss should result in the statistical significance of *ERRVAR*. This is exactly what we find in our results. Our results support the asymmetry in loss functions implied by the findings of prior empirical literature on analysts' incentives, i.e. that analysts are penalized more for positive errors than negative errors. The results reported in Table II are based on a very large sample and unreported analysis reveals that they are extremely robust to various model specification and variable measurement choices (see below).

### Book-to-market and size portfolio analysis

In this section we show that the findings reported above extend to portfolios sorted on *a priori* determinants of analyst forecast bias that are also correlates of forecast error variance and skewness. We consider the relation between forecast errors and *ERRVAR* and *ERSKEW* for portfolios sorted on the basis of book-to-market ratio and on market capitalization. If *ERRVAR* retains its ability to explain within-portfolio forecast errors, this constitutes an even more powerful test of the asymmetric loss function explanation.

We form portfolios on the basis of these stock characteristics first because they are the basis of commonly used investment styles—book-to-market ratio is a common characteristic for distinguishing between value and glamour stocks. Doukas *et al.* (2002) show that analyst forecast bias differs significantly across portfolios sorted on these characteristics (although not in a direction capable of explaining the irrational extrapolation hypothesis). Second, recent research suggests that book-to-market is a useful instrument that captures the degree of accounting conservatism (Beaver and Ryan, 2005) and

[15] Our preferred model excludes the control variables, since models 1–3 emerge from our theoretical analysis. We report the models with control variables only to permit comparison with prior research.

[16] Based on the model of Barron *et al*. (1998), some prior studies (e.g. Gu and Wu, 2003) include cross-sectional dispersion of the consensus forecast as a variable in their regressions to control for 'forecast uncertainty'. We exclude this variable since our predictions are based entirely on the moments of the forecast *error*. Furthermore, the model of Barron *et al*. rests on the assumption of earnings being normally distributed (Barron *et al.*, 1998, p. 423). However, when we estimate our regressions on a subsample where dispersion does not exist (i.e. the standard deviation of the consensus forecast is zero), our results still hold.



**DOI**: 10.1002/for

that conservatism is an important determinant of the distributional properties of earnings and forecast errors (e.g. Basu, 1997; Helbok and Walker, 2004).

We form one-way sorted portfolios each quarter based on beginning-of-quarter book-to-price and on market capitalization. Table III confirms that forecast errors are indeed dramatically different across book-to-market ratio and market capitalization portfolios (a one-way ANOVA tests revealed that the differences between the groups formed on the basis of book to market and size are statistically significant at $p < 0.001$). The mean values of *ERROR* lie between 0.017% for low book-to-market stocks and -0.212% for high book-to-market stocks, indicating that the optimism bias is much higher for high book-to-market stocks. Note also that the standard deviation of *ERROR* increases and the negative skewness decreases monotonically across book-to-market portfolios. In contrast, the stock level estimates of *ERRVAR* and *ERRSKEW* indicate that forecast error variance generally increases with the book-to-market ratio and forecast error skewness is negative and on average decreases with book-to-market. Similar patterns are observed across size-sorted portfolios. The degree of optimism bias in forecasts is much higher for small firms, and *ERRVAR* decreases as firms become larger, as does the extent to which *ERRSKEW* is negative. The patterns of *ERRVAR* and *ERRSKEW* across characteristic portfolios are consistent with the observed forecast error bias.

In Table IV we estimate models 1–3 similarly to Table II, but for the one-way sorted portfolios. The results are generally consistent with Table II.[17] Panel A reports results for portfolios sorted on book-to-market. The coefficient on *ERRVAR* when it is the sole independent variable is negative for all four portfolios, as predicted by the asymmetric loss function explanation, and significant at the 1% level in three of the four groups. Similarly, the coefficient on *ERRSKEW* in model 3 is consistently positive, and significant at the 5% level or better. When both *ERRVAR* and *ERRSKEW* are included in the same regression (model 2), multicollinearity problems become somewhat more severe but *ERRVAR* retains its significance for high book-to-market portfolios (i.e. portfolio BM4) where forecast bias is greatest. In contrast, the sign on *ERRSKEW* changes from positive to negative across portfolios and the coefficient is insignificantly different from zero in three of the four portfolios.

Results in Table IV, panel B, for size-sorted portfolios are similar. *ERRVAR* is negative and significant (at the 5% level at least) for all portfolios in model 1, while *ERRSKEW* is positive and significant at the 5% level for all but the largest firms, where it is significant at $p < 0.10$. When *ERRVAR* and *ERRSKEW* are entered jointly, however, only *ERRVAR* is significant (in two cases at least the 5% level). *ERRSKEW* is statistically insignificant in all four regressions. Again, multicollinearity appears to present a problem for some portfolios, especially in the case of the larger firm portfolios, potentially explaining why *ERRVAR* loses significance when *ERRSKEW* is added.

Overall, the results in Table IV confirm that the variance of forecast errors is a significant determinant of forecast bias, even after first sorting firms into portfolios based on stock characteristics that sharply discriminate between different levels of forecast bias and forecast error variance and skewness. The persistent negative sign and continued significance of *ERRVAR* as an explanatory factor for forecast errors supports earlier research conjecturing that analysts form their forecasts with reference to asymmetric loss functions.

## Robustness checks

The results we have reported are based on price-scaled forecast errors. We believe that there are good reasons for scaling, based on considering the links between forecast errors and the costs

[17] Additional (unreported) tests showed that the results in Table IV are not sensitive to the inclusion of the control variables.



**DOI**: 10.1002/for

Table III. Summary statistics for book-to-market (BM) portfolios and size(S) portfolios

| Panel A: Book-to-market portfolios | *N* | Mean | Median | SD | Skewness |
|---|---|---|---|---|---|
| *ERROR* | | | | | |
| BM1 (low) | 19,669 | 0.0168 | 0.0236 | 0.4277 | −4.65 |
| BM2 | 19,669 | 0.0074 | 0.0229 | 0.4666 | −4.02 |
| BM3 | 19,669 | −0.0290 | 0.0223 | 0.6061 | −3.28 |
| BM4 (high) | 19,668 | −0.2120 | 0.0000 | 1.2077 | −2.12 |
| *ERRVAR* | | | | | |
| BM1 (low) | 19,669 | 0.0396 | 0.0007 | 0.2755 | 10.74 |
| BM2 | 19,669 | 0.0364 | 0.0016 | 0.2552 | 11.71 |
| BM3 | 19,669 | 0.0559 | 0.0038 | 0.3099 | 9.27 |
| BM4 (high) | 19,668 | 0.1703 | 0.0142 | 0.5500 | 4.88 |
| *ERRSKEW* | | | | | |
| BM1 (low) | 19,669 | −0.0013 | 0.0000 | 0.0163 | −13.51 |
| BM2 | 19,669 | −0.0013 | 0.0000 | 0.0154 | −13.96 |
| BM3 | 19,669 | −0.0022 | 0.0000 | 0.0201 | −10.58 |
| BM4 (high) | 19,668 | −0.0071 | 0.0000 | 0.0354 | −5.75 |
| **Panel B: Size portfolios** | *N* | Mean | Median | SD | Skewness |
| *ERROR* | | | | | |
| S1 (small) | 25,040 | −0.2651 | 0.0000 | 1.6156 | −2.88 |
| S2 | 25,040 | −0.0498 | 0.0231 | 0.8563 | −4.51 |
| S3 | 25,040 | −0.0107 | 0.0255 | 0.6767 | −5.63 |
| S4 (large) | 25,040 | 0.0151 | 0.0242 | 0.4932 | −7.33 |
| *ERRVAR* | | | | | |
| S1 (small) | 25,040 | 0.2045 | 0.0135 | 0.6381 | 4.31 |
| S2 | 25,040 | 0.0832 | 0.0041 | 0.4066 | 7.20 |
| S3 | 25,040 | 0.0564 | 0.0023 | 0.3107 | 8.94 |
| S4 (large) | 25,040 | 0.0267 | 0.0009 | 0.2064 | 13.63 |
| *ERRSKEW* | | | | | |
| S1 (small) | 25,040 | −0.0085 | 0.0000 | 0.0396 | −5.13 |
| S2 | 25,040 | −0.0030 | 0.0000 | 0.0240 | −8.99 |
| S3 | 25,040 | −0.0020 | 0.0000 | 0.0191 | −11.05 |
| S4 (large) | 25,040 | −0.0010 | 0.0000 | 0.0137 | −15.63 |

*Notes*:
*ERROR* is actual quarterly earnings taken from I/B/E/S minus the median of all forecasts of quarterly earnings issued within 90 days of the earnings announcement, scaled by stock price at the beginning of the quarter, multiplied by 100.
*ERRVAR* is the second moment of the price-deflated previous eight quarters' forecast errors, multiplied by 100.
*ERRSKEW* is the third moment of the price-deflated previous eight quarters' forecast errors, multiplied by 100.
BM represents book-to-market portfolios (where 1 is the lowest B/M quartile and 4 is the highest B/M quartile).
S represents size portfolios (where S1 comprises the quartile of smallest companies in the full sample and S4 comprises the largest).



**DOI**: 10.1002/for

borne by users of earnings forecasts (as pointed out in note 10 above). However, there is also evidence suggesting that scaling may have perverse effects on the distributional properties of variables (see, for example, Cohen and Lys, 2003; Durtschi and Easton, 2005; Lambert, 2004). For this reason, we also employed the Wild bootstrap methodology to both price-scaled and unscaled data and identified critical values for relevant test statistics (Davidson and Flachaire, 2001). This methodology utilizes the distribution of the error term in the main estimating equation to simulate empirical confidence intervals necessary to reject the null hypothesis when the null holds (see Clatworthy *et al.*, 2007). It provides a powerful test of statistical significance when the underlying regression error distribution is non-normal (Wu, 1986; Hardle and Mammen, 1993). Use of the Wild bootstrap can often result in critical values differing dramatically from classical values. For example, according to our estimates based on 10,000 iterations, critical values to allow rejection of the hypothesis that *ERRVAR* is significantly different from zero are [-7.31] and [7.41] for $p < 0.05$ for unscaled data. Despite such major departures from classical test statistic critical values, in unreported results we find that after taking account of the bootstrapped critical values all the inferences drawn from the main results reported in Table II remain intact (results are available from the authors upon request).

Table IV. Regressions of models 1–3 by book-to-market (BM) portfolios and size (S) portfolios

Panel A: Book-to-market portfolios

| | Model 1 | | | | Model 2 | | | |
|---|---|---|---|---|---|---|---|---|
| | BM1 (low) | BM2 | BM3 | BM4 (high) | BM1 (low) | BM2 | BM3 | BM4 (high) |
| Constant | 0.0238 | 0.0093 | −0.0212 | −0.1679 | 0.0238 | 0.0074 | −0.0226 | −0.1655 |
| | (6.37)*** | (2.31)** | (3.74)*** | (13.82)*** | (6.35)*** | (1.86)* | (3.96)*** | (13.60)*** |
| *ERRVAR* | −0.1789 | −0.0526 | −0.1397 | −0.2591 | −0.1746 | 0.1028 | −0.0586 | −0.3168 |
| | (2.86)*** | (1.19) | (2.96)*** | (7.25)*** | (1.54) | (1.39) | (0.69) | (4.57)*** |
| *ERRSKEW* | — | — | — | — | 0.0876 | 3.0082 | 1.4171 | −1.0434 |
| | — | — | — | — | (0.05) | (2.42)** | (1.13) | (0.98) |
| *N* | 19,669 | 19,669 | 19,669 | 19,668 | 19,669 | 19,669 | 19,669 | 19,668 |
| $R^2$ | 0.0133 | 0.0008 | 0.0051 | 0.0139 | 0.0133 | 0.0034 | 0.0056 | 0.0142 |
| *F*-value | 8.18*** | 1.42 | 8.75*** | 52.62*** | 4.09** | 3.42** | 5.09*** | 26.89*** |

Panel B: Size portfolios

| | Model 1 | | | | Model 2 | | | |
|---|---|---|---|---|---|---|---|---|
| | S1 (small) | S2 | S3 | S4 (large) | S1 (small) | S2 | S3 | S4 (large) |
| Constant | −0.1691 | −0.0288 | −0.0049 | 0.0183 | −0.1719 | −0.0295 | −0.0054 | 0.0184 |
| | (13.61)*** | (4.23)*** | (0.89) | (3.98)*** | (13.21)*** | (4.31)*** | (0.97) | (4.16)*** |
| *ERRVAR* | −0.4698 | −0.2516 | −0.1032 | −0.1188 | −0.4066 | −0.2218 | −0.0707 | −0.1375 |
| | (8.72)*** | (3.52)*** | (2.02)** | (2.03)** | (3.64)*** | (2.28)** | (0.68) | (1.58) |
| *ERRSKEW* | — | — | — | — | 1.1963 | 0.6094 | 0.6652 | −0.3231 |
| | — | — | — | — | (0.70) | (0.40) | (0.43) | (0.25) |
| *N* | 25,040 | 25,040 | 25,040 | 25,040 | 25,040 | 25,040 | 25,040 | 25,040 |
| $R^2$ | 0.0344 | 0.0143 | 0.0022 | 0.0025 | 0.0347 | 0.0144 | 0.0024 | 0.0025 |
| *F*-value | 76.01*** | 12.40*** | 4.09** | 4.14** | 40.29*** | 6.23*** | 2.91* | 2.24 |



**DOI**: 10.1002/for

Table IV. *Continued*

Panel A: Book-to-market portfolios

| | Model 3 | | | |
|---|---|---|---|---|
| | BM1 (low) | BM2 | BM3 | BM4 (high) |
| Constant | 0.0201 | 0.0093 | −0.0241 | −0.1894 |
| | (5.25)*** | (2.28)** | (4.25)*** | (15.13)*** |
| *ERRVAR* | — | — | — | — |
| | — | — | — | — |
| *ERRSKEW* | 2.5280 | 1.5479 | 2.2127 | 3.1948 |
| | (2.37)** | (2.13)** | (3.17)*** | (5.80)*** |
| $N$ | 19,669 | 19,669 | 19,669 | 19,668 |
| $R^2$ | 0.0092 | 0.0026 | 0.0054 | 0.0087 |
| $F$-value | 5.60** | 4.52** | 10.04*** | 33.63*** |

Panel B: Size portfolios

| | Model 3 | | | |
|---|---|---|---|---|
| | S1 (small) | S2 | S3 | S4 (large) |
| Constant | −0.2079 | −0.0387 | −0.0076 | 0.0166 |
| | (15.98)*** | (5.76)*** | (1.29) | (3.51)*** |
| *ERRVAR* | — | — | — | — |
| | — | — | — | — |
| *ERRSKE* | 6.7617 | 3.7251 | 1.5776 | 1.4908 |
| *W* | (8.17)*** | (3.21)*** | (2.27)** | (1.74)* |
| $N$ | 25,040 | 25,040 | 25,040 | 25,040 |
| $R^2$ | 0.0275 | 0.0109 | 0.0020 | 0.0017 |
| $F$-value | 66.80*** | 10.33*** | 5.17** | 3.04* |

*Note*: Models are as reported in columns 1–3 in Table II. S represents size portfolio, where S1 comprises the quartile of smallest companies in the full sample ($N = 100,160$), while S4 comprises the largest. BM represents book-to-market portfolio, where BM1 comprises the lowest quartile of companies with data available ($N$ = 78,675), while BM4 comprises the highest. Dependent variable (ERROR) is actual quarterly earnings taken from I/B/E/S minus the median of all forecasts of quarterly earnings issued within 90 days of the earnings announcement, scaled by stock price at the beginning of the quarter, multiplied by 100. *ERRVAR* is the second moment of the price-deflated previous eight quarters' forecast errors, multiplied by 100. *ERRSKEW* is the third moment of the price-deflated previous eight quarters' forecast errors, multiplied by 100. Asterisks indicate statistical significance at the ***0.01, **0.05 and *0.10 level respectively; absolute $t$-statistics based on firm-clustered standard errors are in parentheses.

Like many other forecast data providers, in order to make data comparable over time, I/B/E/S retrospectively adjusts earnings and forecast data to take account of stock splits and round to the nearest cent. This procedure has been shown to induce conservative measures of forecast errors for firms encountering numerous splits (Baber and Kang, 2002), though it is less problematic for the I/B/E/S Detail Files used in our analysis (Payne and Thomas, 2003). Nevertheless, in order to assess whether this issue affects our results we repeated our analysis on I/B/E/S unadjusted data and our conclusions remain unchanged. Our results also hold when using the most recent forecast, rather than the consensus forecast for each firm quarter.



**DOI**: 10.1002/for

As a further robustness check, we estimated models 1–6 using Fama–MacBeth (1973) regressions. Whereas our main results using standard errors clustered by firm control for possible time series correlation of residuals within companies, the Fama–MacBeth standard errors allow for cross-sectional dependence (i.e. correlations across firms; see Keane and Runkle, 1998). The results (not reported) are again consistent with those reported in Table II and IV. We also employed least absolute deviation (LAD) regression and this yielded results generally consistent with those reported in the tables. The coefficient on *ERRVAR* is consistently significantly negative, though the coefficient on *ERRSKEW* is positive and significant—both with and without the control variables. Although we have no economic rationale for using LAD regression in this context, it still provides a useful robustness test, especially in the presence of data that are known to be non-normally distributed (e.g. Lambert, 2004).

Because of suggestions in prior research that the analysts' loss function parameters may have changed over time, we also conducted our main analysis on separate time periods. More specifically, Hong and Kubik (2003) and Richardson *et al.* (2004) note that the institutional characteristics which lead us to our prediction of asymmetric loss were more pronounced in the 1990s. Furthermore, regulatory changes in the investment industry, coupled with the significant legal settlements with large investment banks that took place at the beginning of the century were designed to increase the costs of issuing biased forecasts and advice (see, for example, Bradshaw, 2009a, 2009b, and Barniv *et al.*, 2009). We therefore estimated our regressions for five-year periods from 1985 onwards and found that the coefficient on *ERRVAR* is smallest in the period 2000–2005, where regulatory attention to conflicts of interest was highest. More specifically, our estimate of the coefficient $\lambda_1$ on *ERRVAR* in model 2 is negative and statistically significant in all periods, except the period 2000–2005, though, as noted by Bradshaw (2009a), we interpret these results with caution since we are not able to unequivocally attribute the observed changes directly to the regulatory changes occurring in that sub-period.

## CONCLUSIONS

In this paper, we test whether analysts' earnings forecasts are consistent with their loss functions being asymmetric. Research based on data from a variety of countries consistently finds evidence of bias and inefficiency in analysts' forecasts of earnings (e.g. Brown, 1993; Capstaff *et al.*, 1995, 1998, 2001). Whether one can conclude that this represents evidence of irrationality requires knowledge of the shape of analysts' loss function (Keane and Runkle, 1998). Some studies have examined the possibility that such findings are attributable to an inappropriate assumption of a quadratic loss function, and concludes that analysts' objective is to minimize the mean absolute forecast error, rather than mean squared error (Gu and Wu, 2003; Basu and Markov, 2004). The mean absolute error loss function penalizes forecast optimism and pessimism equally and the respective explanation for forecast bias is skewness in the distribution of earnings. However, numerous empirical studies suggest that analysts' motives may be driven by the costs associated with under-predicting earnings being higher than the costs of over-predicting earnings, i.e. asymmetric loss functions. Asymmetric loss functions may result from incentives to gain access to management and/or more favourable career prospects for analysts who are systematically optimistic (e.g., Lim, 2001; Hong and Kubik, 2003).

Under the symmetric linear (MAE) loss function, the expected forecast error is a function only of forecast error skewness. In contrast, under asymmetric loss functions, *ex post* error is also a function of error variance. Our results indicate that the symmetric linear loss function can be rejected in favour of asymmetric loss functions. We find that earnings forecast errors are more strongly related to prior forecast error variance than to skewness, indicating that analysts have asymmetric loss functions.



**DOI**: 10.1002/for

Furthermore, the sign on error variance (and hence the direction of the asymmetry) is consistent with a priori expectations from prior research (e.g. Lim, 2001; Hong and Kubik, 2003; Jackson, 2005) showing that the effects of analysts' institutional incentives are to encourage optimistic forecasts.

Our results have potentially important implications for the interpretation of analysts' earnings forecasts by investors. The assumption that analysts' objectives are solely to minimize forecast error might be inappropriate. As pointed out by Lambert (2004), it is investors', rather than analysts', loss functions that are ultimately most important in determining security prices. However, to the extent that analysts' forecasts influence investors' decision making, an understanding of the shape of analysts' loss function is necessary to enable investors to consider adjustment for potential biases.

A limitation of our research design, like those used in prior empirical research into analysts' loss functions, is that it is only able to capture aggregate effects and assumes that the consensus is representative of the 'marginal' analyst. Our design also prevents us from tracking possible changes in loss function parameters over the forecast horizon, even though there is evidence to suggest that they may not be constant (e.g. Richardson *et al.*, 2004). Further research could seek to address such issues in order to identify factors that may cause the extent of the asymmetry in analysts' loss functions to vary, as suggested by Ramnath *et al*. (2008), perhaps using alternative approaches, such as those set out in Elliott *et al*. (2005) and Patton and Timmermann (2007b).

## APPENDIX

Expanding the Linex function (1) to a fourth-order Taylor approximation we obtain

$$L = \frac{(e^{\alpha x_t} - a x_t - 1)}{\alpha^2} \cong \frac{x^2}{2} + \frac{\alpha x^3}{6} + \frac{\alpha^2 x^4}{24} \tag{A.1}$$

Noting that $x \equiv y - f$ and minimizing $L$ with respect to the forecast, we obtain

$$\frac{\mathrm{d}L}{\mathrm{d}f} = x + \frac{\alpha x^2}{2} + \frac{\alpha^2 x^3}{6} = 0 \tag{A.2}$$

Taking expectations of (A.2) we obtain the cubic equation

$$E[x + \frac{\alpha x^2}{2} + \frac{\alpha^2 x^3}{6}] = 0 \tag{A.3}$$

Let $Z = E(y) - f$ and $y - E(y) = \varepsilon$. Noting that

$$x^2 = (y - Ey + Ey - f)^2 = (y - Ey + Z)^2 \text{ and}$$
$$x^3 = (y - Ey + Ey - f)^3 = (y - Ey + Z)^3$$

we obtain

$$Z + \frac{\alpha}{2}(\sigma_\varepsilon^2 + Z^2) + \frac{\alpha^2}{6}(\sigma_\varepsilon^3 + 3\sigma_\varepsilon^2 Z + Z^3) = 0 \tag{A.4}$$

where $\sigma_\varepsilon^3 = E(\varepsilon^3) = E(y - E(y))^3$.

Rearranging (A.4) we obtain equation (4) in the text. Note that if we approximate (A.1) to order 3 we obtain

$$Z + \frac{\alpha}{2}(\sigma_\varepsilon^2 + Z^2) = 0$$

Therefore $Z + \frac{\alpha}{2}Z^2 = -\frac{\alpha}{2}\sigma_\varepsilon^2$.

If $\alpha > 0$ then $Z$ becomes more negative—and hence optimism bias increases—as the forecast error variance increases. In other words, the degree of optimism is a positive function of the forecast error variance. This is consistent with the closed-form result of Christofferson and Diebold (1996, 1997) in expression (3).

Expression (A.4) can be rewritten as follows:

$$Z + \frac{\alpha^2}{2}\sigma_\varepsilon^2 Z + \frac{\alpha}{2}Z^2 + \frac{\alpha^2}{6}Z^3 + \frac{\alpha}{2}\sigma_\varepsilon^2 + \frac{\alpha^2}{6}\sigma_\varepsilon^3 = 0 \tag{A.5}$$

If the sum of the last two terms in (A.5) is positive, then the equation has two complex roots and one real root. By inspection, *ceteris paribus*, irrespective of the sign of $\alpha$, $Z$ is a negative function of $\sigma_\varepsilon^3$ (and optimism bias is a positive function of $\sigma_\varepsilon^3$).

In other words, the signs on the coefficients on both forecast error variance and forecast error skewness should be negative for $\alpha > 0$. Note that if forecast error skewness is negative, skewness will partially offset the optimism bias induced by forecast error variance. However, generally, the marginal impact of skewness will be dominated by the variance effect when $|\alpha| < 1$.

Note that while the above analysis has been conducted in the context of the Linex loss function, it is applicable to any continuous asymmetric loss function that is expandable to order four. Such cases will generate a quartic expression analogous to expression (A.1) and hence forecast error variance and skewness will be determinants of bias.

It should be noted also that this analysis also implies that for some symmetric loss functions, forecast error variance and skewness will also be determinants of bias when forecast errors exhibit skewness. An example is the symmetric loss function

$$L = \frac{x^4}{4} \tag{A.6}$$

In this case $Z$ is obtained as a solution to the equation

$$\sigma_\varepsilon^3 + 3\sigma_\varepsilon^2 Z + Z^3 = 0 \tag{A.7}$$

Given this, strictly interpreted, our empirical finding that both variance and skewness are significant determinants of forecast bias only implies inconsistency with the MAE loss function. However, arguments for a symmetric, non-quadratic loss function other than the MAE form have, as yet, not been proposed, to the best of our knowledge.

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**DOI**: 10.1002/for

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